Reproducing Nutriscore: A Machine Learning approach

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Task description

We'd like to see if we can predict Nutriscore from foods using the OpenFoodFacts API. With a suite of clustering and classification models, we'd like to work backwards to see if we can work out what determines Nutriscore. While this exercise seems pointless in itself, the same technique could be used to work backwards to calculate closed source indices, such as those used by financial industries.

We'll try a naïve approach to start with, using nutritional factors to predict Nutriscore using an array of unsupervised clustering techniques to see if they form natural groups. [1]

Afterwards, we'll use supervised classification techniques to create Nutriscore models. We'll cross-validate them and check them against a validation set.

[1] If these groups exists, I suspect this is how the index was created in the first place.

Data description

Our initial plan was to use python `openfoodfacts` library to pull in data directly from the API. Unfortunately, the API was unreliable and had frequent down periods. We opted to use a predownloaded dump of the OpenFoodFacts data from Kaggle. The kaggle data comes in the form of a zipped tab-separated file (.tsv). When extracted, it's about 1GB in size and contains 356 027 rows and 163 columns.

Processing

In order to start using this data, we first had to filter and process it.

Nutriscore is one dimension available on OpenFoodFacts among others, including nutritional data per 100g [2]:

- Energy (kJ)
- Protein
- Sugar
- Sodium
- Salt
- Saturated fat
- Fat
- Carbohydrates

[2] We chose these nutrients as they're the most common ones to find in nutritional information. Stepping out of these moves you from 90% of foods having them, to 90% without.

It also contains tags for all foods, making it easy to specify food types. Calculating the Nutriscore values for everything would be tedious and take a long time to analyse so we're going to look at a few products:

- Breakfast cereals
- Iced teas[3]
- Biscuits and cakes

[3] Iced tea varies a lot in sugar content as it's often geared to the health market and so has options with either low sugar, or where some of the sugar has been replaced with artificial sweeteners.

All of these foods are highly variable in sugar and fat content so it should give us an idea of what causes Nutriscore to change.

Filtering

Even after reducing our dataset, we still noticed some unusual values. In particular, we noticed some salt contents that were peculiarly high.[4] We chose to remove all values with higher than 2% salt and the corresponding value for sodium.[5]

Given that the data we had retained was relatively complete, we opted to discard any rows with missing values rather than imputing. This caused a loss of ~15% of our data.

[4] Hello Panda may not be the healthiest treat, it's unlikely to contain more than its own weight in salt.

[5] Table salt is ~40% sodium, so our threshold was $(2 \times 0.4 = 0.8)$

Exploration

Nutrients

The first thing to look at when you have a new dataset is distribution. Let's look at overall distributions of each of our dependent variables.

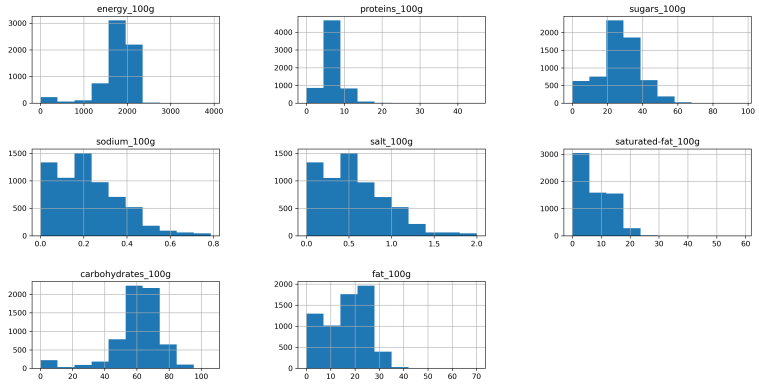

Figure 1: Nutrient distributions of biscuits, iced tea and breakfast cereals

A number of these have large outliers, but after sodium and salt were taken out in the processing step, none of them seem too terrible.[6]

The next stage of describing out nutrients would be to split these by type of food.

[6] Turns out the reason there's a huge outlier here is the presence of some dried coconut that counts as a biscuit. We didn't remove it as there are a number of biscuits from Brittany not too far away with astonishing levels of saturated fats.

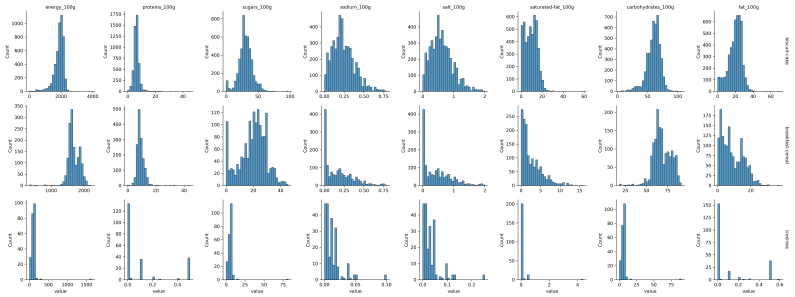

Figure 2: Nutrient distributions of a subset of food categories

There are some very clear patterns in the nutrient distributions of food category.[7] Iced tea behaves quite differently to the others as it has virtually no nutrients other than sugar and energy. Biscuits seem to have the most normally distributed nutrients, while cereals seem to have a number of healthy ones with low sodium and fat but a large spread with more of those nutrients.

[7] Please note that the x-axes are free. I wasn't able to fix it per column and it would have been pointless to fit it for the whole grid.

Nutriscores

Now that we've looked at the nutrients, we'll turn our attention to the Nutriscores.

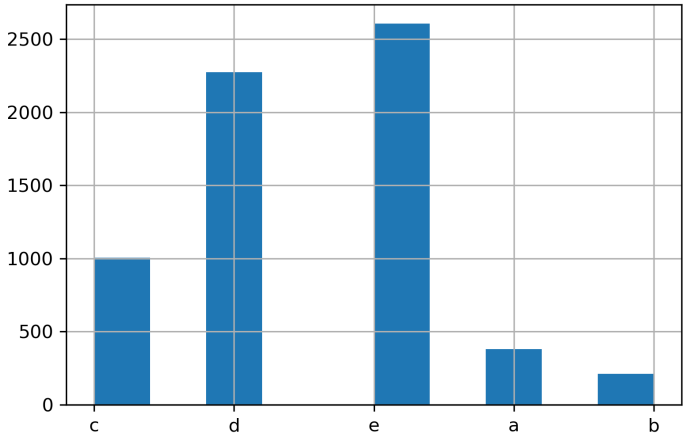

Figure 3: Nutriscore distribution in our data

Out data is mostly unhealthy food, it would seem. We have a lot of foods with scores of D and E, but not so many with scores of A and B. Given that most of the data in OpenFoodFacts is processed food, this isn't surprising - but our choices of category are certainly not helping our cause.

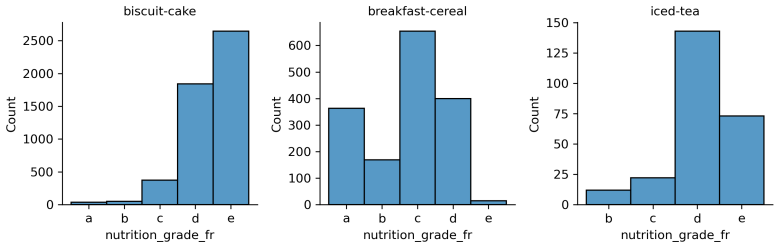

Figure 4: Nutriscore distribution by food

Splitting up the Nutriscores by category, we can see that iced teas are generally unhealthy, with not a single one getting a score of A. Biscuits and cakes show an expected distribution as do breakfast cereals as there's a lacuna between All-Bran and Coco Pops.[8]

[8] I suspect that the reason that there are so many Cs are unhealthy cereals adding fibre to their cereals to get to the first "healthy-ish" tier.

Unsupervised clustering

The first question we wanted to answer was "Do Nutriscores form natural groups?". While there is obviously an underlying model linking foods to Nutriscores, the question could be otherwise formulated: "If a machine creates clusters without knowledge of Nutriscores, will the clusters resemble Nutriscores?"

Method

We chose 10 unsupervised clustering models:

- MiniBatch KMeans
- Affinity propagation
- MeanShift
- Spectral clustering
- Agglomerative clustering (Ward linkage)

- Agglomerative clustering (average linkage)
- DBSCAN
- OPTICS
- BIRCH
- Gaussian mixture

Where possible, we limited them to 5 clusters. We then ran the models on our training data and compared them to our nutriscores. As there's no actual mapping between which cluster corresponds to which score, we've created heatmaps normalising the correspondences[9] by nutriscore and with rows rearranged using hierarchical clustering.

[9] If you don't normalise the correspondences, you'll end up with really low values for clusters with few members, even if the correspondences are good.

Results

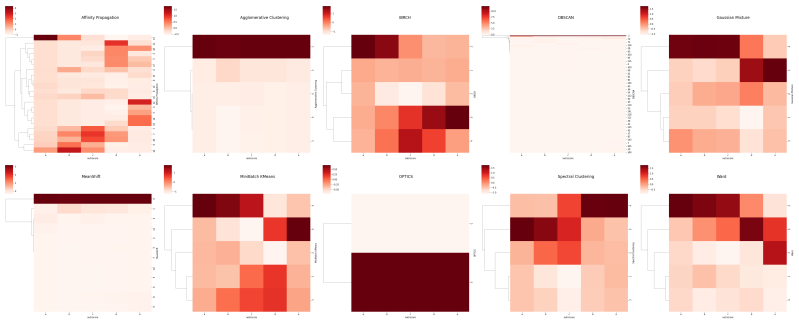

Figure 5: Clustering results

There's a lot to break down here. The models that performed poorly:

- Agglomerative clustering (average linkage)
- DBSCAN
- MeanShift
- OPTICS

These models tended to push everything into one cluster. It might be possible to fix this by adjusting the parameters.

The other models seemed to able to cleanly split scores A and B from D and E (Agglomerative with Ward, Spectral and Gaussian mixture). Affinity propagation is worth further investigation as

while it has multiple clusters, it seems to have a cluster which identifies each Nutriscore.

Conclusion

Given that these we found in an unsupervised manner, it's safe to say that Nutriscores are natural groupings found in the data.

Classification

We looked at 6 classification models:

- K nearest neighbours
- Random forest
- Decision tree
- Linear SVM[10]
- SVM with RBF
- Ridge regression

Each of these models was run with default parameters in `sklearn` and cross-validated using a 5-fold method. 20% of the dataset was randomly selected as a validation set in addition to the cross-validation. All

[10] We had to reduce the regularisation parameter (C) to 0.01 for both SVM models as the default value of 1 was taking hours to fit. In retrospect perhaps `max_iter` would have been a better choice.

Cross-validation results

The SVM models performed particularly poorly - both in their training and during the cross-validation. This is almost certainly because we had to cripple them with low regularisation parameters or else they simply took too long to run.

Ridge regression is notable for having very similar values for training and cross-validation. There's no overfitting, but its overall performance with its current parameters is too low to consider.

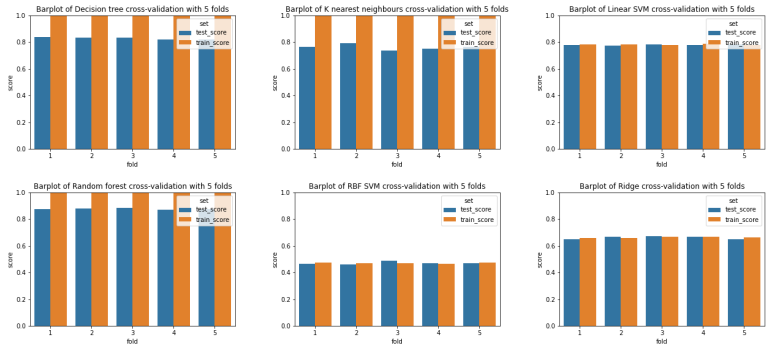

Figure 6: Cross-validation of all classification models using 5 folds

K nearest neighbours, decision trees and random forests had near perfect performance on their training sets and good performance in cross validation. The winner is clearly *random forest*, having the highest cross-validation scores.

Validation

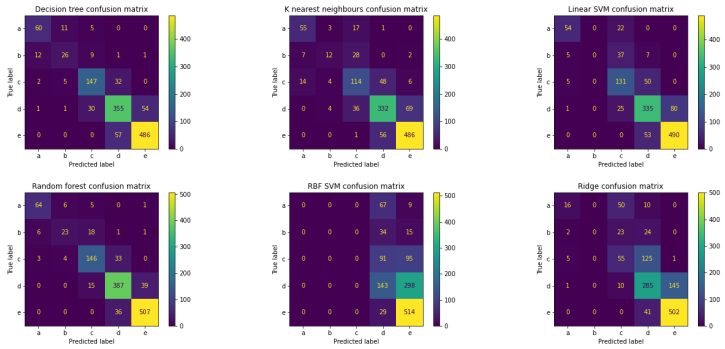

Figure 7: Unnormalised confusion matrices for each of the models predicting Nutriscore from nutritional information

A quick glance it seems that everything does a really good job except for RBF and Ridge which was somewhat expected given their cross-validation results. They don't predict very well for the small groups: Nutriscore A and B.

Normalising these results will allow us to get a better idea of the prediction accuracy for these smaller groups.

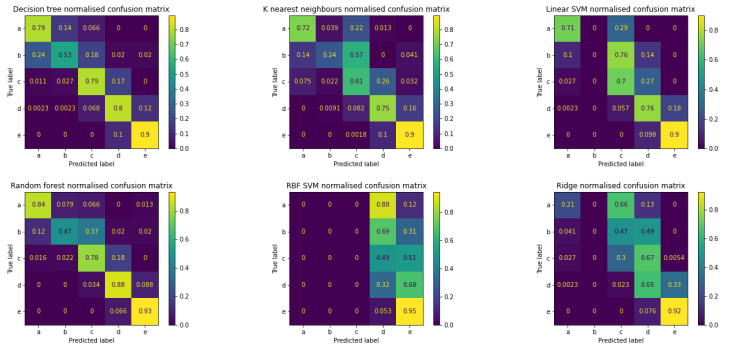

Figure 8: Normalised confusion matrices for each of the models predicting Nutriscore from nutritional information

With the normalisation of the confusion matrix, we can better see the prediction quality. Ridge and RBF are of course chronically underpredicting for the healthier classes. We can clearly see that decision trees and random forests give the best predictions of Nutriscore for all levels.

Linking back to the nature of Nutriscore

We saw in the previous section that tree/decision models gave the best results, but why is that? Our theory is that these models best describe the underlying calculation. Our hypothesis is that the actual calculation relies on logical splits based on nutrients.

The actual calculation is given by official sources in notoriously unhelpful documents such as the password-protected spreadsheet from Santé Publique France.

Fortunately, some developers have taken it upon themselves to make more useful forms of it, in particular the developer of the nutri-score js library who wrote out the calculation below.[11]

Of major note is the last line containing the following equation[12]:

[11] Taken from `nutriScore.js` in `nutriscore` that gives a full calculation of Nutriscore.

[12] I'm really bad at javascript so I have no idea if my newlines I needed to make it fit the page made it invalid

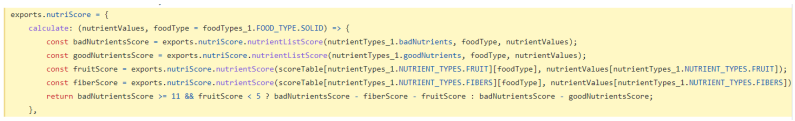

Figure 9: Code for nutriscore calculation

```
badNutrientsScore >= 11 && fruitScore < 5 ?
  badNutrientsScore - fiberScore - fruitScore :
    badNutrientsScore - goodNutrientsScore
```

Translated into something more Pythonic:

```
if (badNutrientsScore >= 11 and fruitScore < 5):
  nutriscore = badNutrientsScore - fiberScore - fruitScore
else:
  nutriscore = badNutrientsScore - goodNutrientsScore
```

The total calculation is more complex, but it's clear why decision tree-type models seem to do well.

Conclusions

Nutriscore is reverse-engineerable. Clustering algorithms that do well at identifying Nutriscore groups are Agglomerative clustering (Ward), Spectral clustering and Gaussian Mixture. Classification algorithms that do a good job tend to be the decision tree models such as decision trees themselves and random forest models.

Future improvements

There are of course a number of changes that could be made to improve this analysis[13]:

- Find more foods with Nutriscore A and B
- Perform Feature importance to to more easily find which variables are more important

[13] We *could* have added more things - but aren't you tired of reading it already?

- Normalising variables may have led to better results for sodium/salt
- Searching variable space to optimise parameters
- Create an easily-interpretable model of Nutriscore